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ORIGINAL ARTICLE

Implications for spatial non-stationarity and the neighborhood effect averaging problem (NEAP) in green inequality research: evidence from three states in the USA

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Abstract

Recent studies on green space exposure have argued that overlooking human mobility could lead to erroneous exposure estimates and their associated inequality. However, these studies are limited as they focused on single cities and did not investigate multiple cities, which could exhibit variations in people's mobility patterns and the spatial distribution of green spaces. Moreover, previous studies focused mainly on large-sized cities while overlooking other areas, such as small-sized cities and rural neighborhoods. In other words, it remains unclear the potential spatial non-stationarity issues in estimating green space exposure inequality. To fill these significant research gaps, we utilized commute data of 31,862 people from Virginia, West Virginia, and Kentucky. The deep learning technique was used to extract green spaces from street-view images to estimate people's home-based and mobility-based green exposure levels. The results showed that the overall inequality in exposure levels reduced when people's mobility was considered compared to the inequality based on home-based exposure levels, implying the neighborhood effect averaging problem (NEAP). Correlation coefficients between individual exposure levels and their social vulnerability indices demonstrated mixed and complex patterns regarding neighborhood type and size, demonstrating the presence of spatial non-stationarity. Our results underscore the crucial role of mobility in exposure assessments and the spatial non-stationarity issue when evaluating exposure inequalities. The results imply that local-specific studies are urgently needed to develop local policies to alleviate inequality in exposure precisely.

Keywords Exposure · Green space · Inequality · Spatial non-stationarity · Street-view images

JEL Classification I140 · R140 · R400

Extended author information available on the last page of the article

1 Introduction

Studies on environmental health and health geography have demonstrated that green space is important in improving people's mental and physical well-being. For instance, previous studies have linked exposure to green space with reduced risk of stress (Lafortezza et al. 2009; Nielsen and Hansen 2007; Thompson et al. 2012), reduced cardiovascular diseases (Gascon et al. 2016; Shen and Lung 2017), and reduced psychosocial disorders (Beyer et al. 2014; Maas et al. 2009; Mackay and Neill 2010; McCaffrey 2007). In addition to health benefits, green spaces offer a myriad of social and environmental benefits, such as alleviating air and noise pollution (Datzmann et al. 2018; Van Renterghem 2019), combating urban heat island effects (Ke et al. 2021), improving urban ecosystems (Kendal et al. 2020), and creating opportunities for social interaction (Bijker and Sijtsma 2017; Orban et al. 2017).

Moreover, researchers have investigated the inequitable distribution of green space and its associated health benefits. Chen et al. (2022) concluded that people living in cities of the Global South experience merely one-third of the exposure to green spaces of people living in the Global North. In the USA, empirical studies have shown that low-income communities and minorities are less exposed to green spaces (Dai 2011; Hoffimann et al. 2017; Kim et al. 2023; Rigolon 2016; Spotswood et al. 2021). For instance, a recent study by Kim et al. (2023) showed an uneven distribution of green space between White and African-American residents of an urban area. They found that the positive correlation between greenness and biological aging based on DNA changes existed only among white residents. In a study of Baltimore, Maryland, Boone et al. (2009) concluded that even though Black residents have greater access to parks, the parks near their neighborhoods are inferior in quality to those of parks in White neighborhoods.

Early efforts to identify individuals' exposure to green spaces have used remote sensing data, such as the normalized difference vegetation index (NDVI) to identify green spaces (Akpinar et al. 2016; Du et al. 2017; Khan et al. 2021a; Lin et al. 2023; Schoepfer et al. 2005; Su et al. 2019; Qian et al. 2019). However, remote sensing images are captured by airborne or spaceborne satellite sensors, which may not accurately capture green spaces at a scale reflecting people's daily experience and eye-level perspective (Jiang et al. 2017; Li et al. 2015; O'Regan et al. 2022; Yang et al. 2009). Additionally, many previous studies assumed that people do not move around (Chen et al. 2022; Su et al. 2019) and, therefore, failed to assess dynamic exposure that considers people's daily mobility. In reality, people routinely travel to work, shop, and exercise in neighborhoods distant from their homes (Farber et al. 2012; Hanson and Hanson 1981; Kwan 2012, 2013, 2018a, b).

Recent studies have considered human mobility when estimating individuals' green space exposure to examine how and to what extent overlooking human mobility leads to erroneous results. For instance, by utilizing survey data of 554 people living in a selected neighborhood in Beijing, Wang et al. (2021) concluded that people with limited exposure to green spaces in their work environment compensate for this deficiency by increasing their interaction with green spaces at trips beyond their workplace. Utilizing the 2008 Montreal Household Travel Surveys data, Reyes et al. (2014) observed that more public parks are accessible to children from higher-income than from lower-income families, primarily due to the greater mobility of higher-income children. Yoo and Roberts (2022) gathered activity-travel data of 1911 people living in the Buffalo (New York) metropolitan area and found that despite a statistically significant association between a person's mobility and exposure to green space at home, this relationship is influenced by both personal and temporal modifiers. For example, the similarity between mobility-based and home-based green space exposure was less pronounced for employed than for unemployed people, whereas this correspondence was stronger on weekends. These studies have concluded that levels of exposure to dynamic green space differ from static exposure levels that do not consider daily mobility.

Beyond simply arguing that static exposure approaches are erroneous because they fail to consider human mobility, Kwan (2018a) identified specific patterns in the discrepancies between the two exposure assessment approaches: the neighborhood effect averaging problem (NEAP). The NEAP, a crucial methodological issue in exposure assessment studies, argues that overlooking human mobility can lead to erroneous exposure assessments (Kwan 2018a). This is because static exposure assessments do not take into account the neighborhood effect averaging effect caused by human mobility (Kwan 2018a). The averaging effect indicates that levels of individual home-based (static) exposure tend to converge with the population's average level of exposure when human mobility is considered (Kwan 2018a). Therefore, an important implication of the NEAP is that the static approach can lead to inaccurate evaluations of disparities in green exposure levels between two different sociodemographic groups. This is particularly because of the level of differences in interactions between individuals' sociodemographic characteristics and the level of the neighborhood effect averaging they experienced (Kim and Kwan 2021a, 2021b; Ma et al. 2020; Wang et al. 2024).

After the introduction of NEAP, it became the topic of a growing number of exposure assessment studies (e.g., Huang and Kwan 2022; Kim and Kwan 2019, 2021a; Kwan 2018a; Ma et al. 2020; Tan et al. 2020; Wang et al. 2024). Wang et al.'s (2024) Beijing case study found that people with large activity spaces (e.g., employed and younger people) would experience the NEAP in their exposure to green spaces more than their counterparts with smaller activity spaces. However, another Beijing case study arrived at the opposite conclusion, indicating a polarization effect rather than an averaging effect because of individuals preferred visiting more environments that had greenery (Wu et al. 2021). Although these empirical studies on NEAP in green space exposure have laid the foundation for future studies, two important limitations should be addressed.

The first limitation is that prior attempts to examine and address the NEAP focused on one or a few local neighborhoods (e.g., Wang et al. 2021, 2024; Yoo and Roberts 2022). However, there has been a growing acknowledgment that human–environment interactions, particularly those linked to human preferences, decision-making, and behaviors, may exhibit spatial variability (Fotheringham and Sachdeva 2022).

Specifically, since the complex interactions between people's daily mobility (e.g., where individuals live and work) and the spatial distribution of green spaces might differ across cities, any conclusions based on one or a few neighborhoods in one area might not apply elsewhere, which is referred to as the spatial non-stationarity (Brunsdon et al. 1996; Gilbert and Chakraborty 2011; Mennis and Jordan 2005). For example, Lin et al. (2023) revealed that associations between the availability of green spaces and the selected health outcome (e.g., rates of COVID-19 infection) vary in cities of different sizes (e.g., large central metro vs. small metro areas), suggesting spatial non-stationarity. Focusing on two cities in Chile, Rojas et al. (2016) revealed that residents of the city center of Temuco had the most access to urban green spaces, whereas residents of Valdivia, characterized by shorter walking distances, had less. Although these studies did not directly examine the NEAP, their findings might suggest the presence of spatial non-stationarity in the NEAP, which has yet to be investigated. Thus, results obtained from one global model would be substantially different from those obtained from local models.

Second, previous studies that attempt to examine and address the NEAP largely focused on big cities, such as Beijing (Wang et al. 2021, 2024; Wu et al. 2022; Xu et al. 2023), Shanghai (Li et al. 2023), Shenzhen (Xie et al. 2023), and Buffalo (Yoo and Roberts 2022). Given that many people live in rural areas, towns, or small- and medium-sized cities (e.g., Kim and Jang 2023; Kim and Lee 2023), findings based on large metropolitan areas could be of limited generalizability when formulating environmental policies related to green space inequality (Kwan 2021). By incorporating insights from diverse geographical contexts, we can better address the complex interplay among the social, economic, geographic, and environmental factors shaping green space inequality, ultimately fostering healthier and more sustainable communities.

In summary, existing studies on individuals' green space exposure have not fully addressed the two limitations, which remain critical knowledge gaps. To bridge these significant research gaps, our research evaluates disparities in people's mobility-based exposure to green space by utilizing mobility data from 31,862 people and their associated street-view image data obtained from three states—Virginia, West Virginia, and Kentucky—in the USA. We purposefully selected these three adjacent states because the study area consists of big cities (e.g., the Northern Virginia and Louisville region) and medium-sized cities (e.g., Charleston, Lexington, and Roanoke). Moreover, our study area includes less-studied smaller cities and rural areas in the Appalachian Mountains, which makes it appropriate to investigate green space exposure inequalities in diverse geographic contexts and to examine spatial non-stationarity issues in the NEAP. In other words, by encompassing diverse urban and rural settings across multiple states, our results can offer insights into the NEAP in green space exposure and into the disparities that may be more generalizable and applicable to a wider range of geographic contexts.

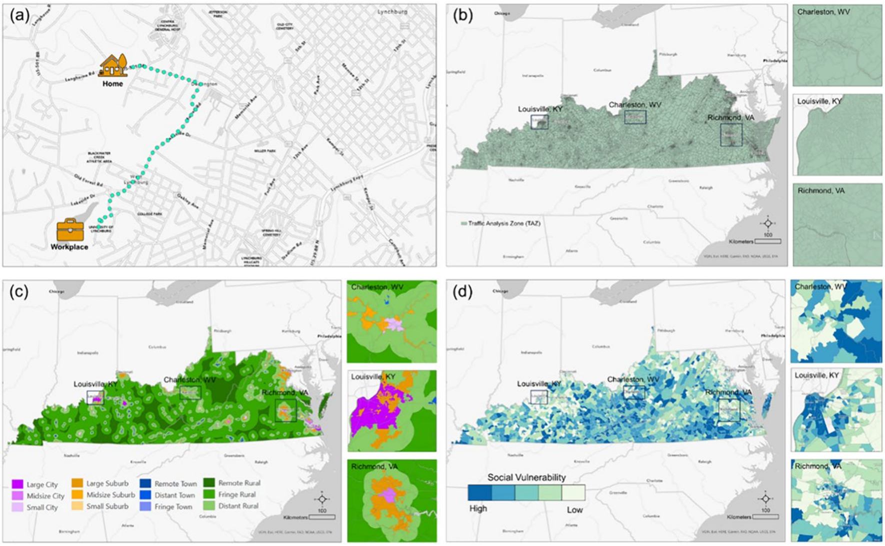

Fig. 1 **a** Walk-based home-work pattern of a sample individual in the Lynchburg Area, Virginia; **b** Traffic Analysis Zone (TAZ) of the study area **c** Neighborhood classification by types and sizes of the study area; **d** Social Vulnerability Index (SVI) of the study area

2 Data and methods

We used commute trip origin–destination data provided by the 2012–2016 US Census Transportation Planning Products (CTPP). The CTPP data provide the home and work locations of walk commuters aggregated at the traffic analysis zone (TAZ). The data were aggregated at a TAZ level as shown in Fig. 1b because of the geoprivacy of the sampled individuals. Even though the data for each individual is aggregated, the granularity at the TAZ level remains sufficiently detailed to capture individuals' travel behaviors (e.g., Bwire and Zengo 2020; Ding 1998; Kim and Jang 2023). This study focused on walk trips, a mode of physically active transportation (Haybatollahi et al. 2015), which potentially provides more interaction with green space (Ta et al. 2021) than other modes of transportation, such as driving.

The final sample consists of 31,862 walk commuters for the study area. Figure 1a shows the walk-based commute trajectory of one of the walk commuters in Lynchburg, Virginia, as an illustrative example. The commuter trips that reported exceptionally excessive travel time (i.e., more than 60 min of walking) and intra-zonal trips (i.e., trips within the same TAZ) were excluded from the sample (1230 out of 3636 trips for VA, 317 out of 855 trips for WV and 802 out of 1820 trips for KY). Next, we estimated individual samples' walk-based commute trajectory by utilizing the Google Maps Direction API, assuming that people follow the shortest travel time path that is based on the real-world pedestrian network (e.g., sidewalks, trails) from the home TAZ's centroid to the workplace TAZ's centroid.

The selection of Google Maps Direction API was based on a comprehensive evaluation of three possible options: Google Maps, OpenStreetMaps, and pedestrian network data from each city. Google Maps Directions API, renowned for its comprehensive and user-friendly interface (Kim and Kwan 2021a, 2021b; Park 2020), was the most accessible and reliable dataset. While OpenStreetMap is widely utilized, its inherent inconsistencies posed significant challenges (Herfort et al. 2023; Zhang and Malczewski 2018) particularly for underrepresented neighborhoods, rural towns and small cities (Herfort et al. 2023). Additionally, the prospect of individually obtaining pedestrian network data from each local region was impractical for our purposes because our study consists of towns and cities in three states. For these reasons, we selected Google Maps to estimate people's commute walking trajectories.

The Green View Index (GVI), proposed by Yang et al. (2009), was utilized to estimate levels of home- and mobility-based green space exposure. For all locations comprising the sample's walk-based commute trajectories, we computed GVI as follows. First, Google Street View (GSV) images were downloaded in the four cardinal directions along the walk-based commute trajectory points of each individual. The extraction of greenspaces from the 360° streetscape images was achieved using semantic segmentation, a deep learning technique increasingly employed in research for categorizing every pixel in an image (Chen et al. 2022). We used the Xception model (Chollet 2017), which has been trained using the ADE20K dataset (Zhou et al. 2017). Based on the classification of the Xception model, the pixels covered by trees, palms, plants, and grass were categorized as green pixels. The Green View Index (GVI) was then calculated as the ratio of the green pixels to the total pixels in each image, as shown in Fig. 2.

We used two methods of calculating the green space exposure for individual samples. The first approach was to determine the green exposure value at the point of origin of their commute and corresponds to the centroid of the commuter's home location TAZ; we refer to this as home-based green space exposure.

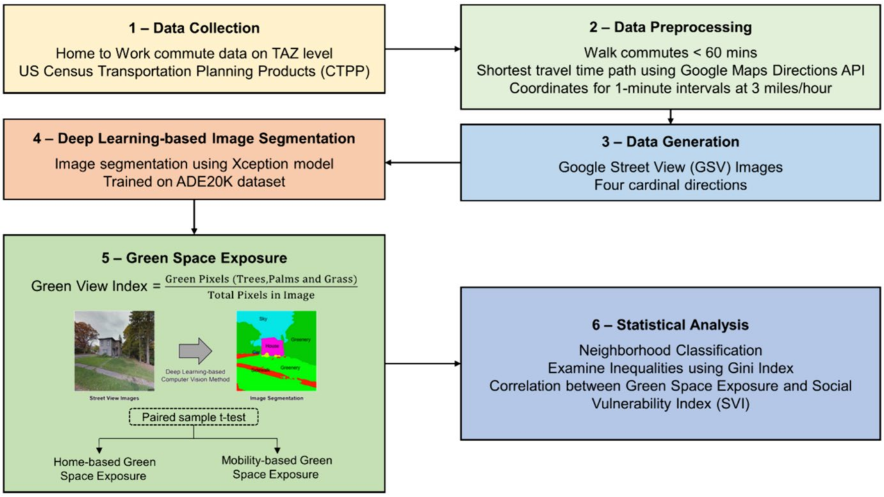

Fig. 2 An overview of the research method to estimate individuals' walk-based commute trajectories of 31,862 commuters in the sample obtained from the three states

The second approach, mobility-based green space exposure, encompassed calculating the average of the green exposure values encountered along the commuter's walking-based commute trajectory. Both the home- and mobility-based exposure measurements for an individual were essential parameters for further analyses. To assess differences between the two green space exposure measures, we conducted a paired sample t-test.

The study area was classified based on the individuals' residential neighborhoods using the National Center for Education Statistics (NCES) data to study urban–rural disparity in green space exposure. The four types of neighborhood classification—Rural, Town, Suburban, and Urban—were included for classifying the samples' residential neighborhoods, as seen in Fig. 1c. The categorization of the urban territory as a single group is often overly generalized, and it can result in overlooking significant variations in geographic contexts, mobility patterns, and associated health conditions (Ingram and Franco 2014). Therefore, we sorted urban and suburban categories into three subtypes—large, medium, and small metro—based on size and population of the neighborhood, leaving us with seven classification types (Table 1).

Next, we computed the Gini index to examine the inequalities in people's exposure to green spaces. While the Gini index is primarily used to assess income inequality, it has been applied to measure disparities in the distribution of green space (Chen et al. 2022; McDonald et al. 2010; Song et al. 2021). The value of the Gini coefficient ranges from 0 to 1, where 0 represents absolute equality in exposure to greenspace, and 1 illustrates absolute inequality (Gini 1921). We then computed correlation coefficients between individuals' green space exposure and the Social Vulnerability Index (SVI). The SVI integrates 16 social factors, including racial and ethnic minority status, unemployment, and disability, offering a comprehensive assessment of socioeconomic disparities and has been widely adopted as a measure of social vulnerability in the USA (e.g., Khan et al. 2021b; Rha et al. 2023; Rufat et al. 2019; Thompson et al. 2022). The SVI was obtained from the US CDC/ATSDR (Agency for Toxic Substances and Disease Registry) for 2020 at block group level. Our analysis used a composite index derived from the data, with values ranging from 0 (low social vulnerability) to 1 (high social vulnerability). Figure 1d illustrates the SVI values of the study area. Although it would be ideal to estimate regression models to control covariates (rather than correlation analyses), we could not estimate regression models since individual-level detailed sociodemographic data are not available due to concerns with data privacy. Future studies can compensate for this limitation by obtaining individual-level household travel survey data.

When computing correlation coefficients, we treated both home- and mobility-based green exposure as dependent variables, while the SVI score obtained from the sample's home location served as the independent variable. Gini indices and correlation coefficients were obtained for the entire sample and the subsample regarding the neighborhood type and size to examine the spatial non-stationarity of the relationship between green space exposure and social vulnerability levels. For instance, certain neighborhood types and sizes would report stronger relationships between SVI and green space exposure than others would, indicating the presence of spatial-nonstationary.

Table 1 Descriptive statistics of one-way commute length and social vulnerability index (SVI) of individual walk commuters in the sample

	Description	Average commute time (minutes)	Social vulnerability index (SVI)
Entire sample ($n = 31{,}862$)		26.36 (19.58)	0.590 (0.359)
Neighborhood type			
Urban ($n = 22{,}108$)	Territory inside an urbanized area and a principal city	23.99 (19.42)	0.588 (0.361)
Suburban ($n = 7120$)	Territory inside an urbanized area and outside a principal city	29.76 (18.98)	0.577 (0.359)
Town ($n = 2225$)	Territory inside an urban cluster	35.20 (18.04)	0.637 (0.333)
Rural ($n = 409$)	Census defined rural territory	47.42 (13.97)	0.727 (0.241)
Neighborhood size			
Large ($n = 10{,}497$)	Urban and Suburban areas with population greater than or equal to 250,000	27.02 (18.95)	0.580 (0.349)
Medium ($n = 8954$)	Urban and Suburban areas with population less than 250,000 and greater than or equal to 100,000	22.66 (19.40)	0.498 (0.357)
Small ($n = 9777$)	Urban and Suburban areas with population less than 100,000	29.76 (19.98)	0.668 (0.352)

Standard deviations in parentheses

3 Results

3.1 Descriptive statistics of individual walk commuters' green exposure levels

Table 2 presents the descriptive statistics of individual walk commuters' home- and mobility-based levels of green exposure. Recall that home-based exposure levels indicate green exposure levels in the sample's home location, and mobility-based exposure levels indicate green exposure levels in the sample's walk-based home-to-work trajectories. As seen in Table 2, the paired sample t-test indicates a significant difference in average green exposure levels between the home- and mobility-based approaches ($p<0.001$). Specifically, the average green exposure level for the home-based approach is 29.389 (%), whereas for the mobility-based approach is 25.092 (%). This indicates a decrease of approximately four percentage points in individuals' average green exposure level during their commuting compared to their exposure at home neighborhoods.

Figure 3 presents specific patterns of the difference between individual home- and mobility-based levels of green exposure. Figure 3a, which illustrates the probability density function of individual green exposure levels, demonstrates a tendency to converge toward the mean exposure levels in the mobility-based approach. Figure 3b, which illustrates the box plot of individual exposure levels, corroborates the convergence that is observed in the probability density function. Overall, our findings based on analyzing the entire sample ($n=31,862$) suggest individual mobility-based exposure levels tend more to the population's mean level of green exposure, which is evidence for the existence of NEAP.

The analysis of the average levels of green exposure for different neighborhood types (i.e., urban, suburban, town, and rural neighborhoods) and sizes (i.e., large, medium, and small urban and suburban neighborhoods) yielded similar results

Table 2 Descriptive statistics of walk commuters' home- and mobility-based green exposure levels

	Home-based green exposure levels	Mobility-based green exposure levels	Difference
Entire sample ($n=31,862$)	29.389 (15.557)	25.092 (9.292)	4.297***
Neighborhood type			
Urban ($n=22,108$)	28.087 (15.626)	23.917 (8.982)	4.170***
Suburban ($n=7120$)	31.756 (14.922)	28.760 (6.956)	2.996***
Town ($n=2225$)	32.290 (13.513)	26.950 (9.840)	5.340***
Rural ($n=409$)	42.860 (19.400)	36.200 (9.395)	6.660***
Neighborhood size			
Large ($n=10,497$)	31.039 (16.343)	25.576 (8.550)	5.463***
Medium ($n=8954$)	27.079 (16.295)	22.408 (8.521)	4.671***
Small ($n=9777$)	28.510 (15.349)	25.739 (9.454)	2.771***

*** denotes $p<0.001$ (paired sample t-test). The exposure level of a certain location in an individual's walk-based commute trajectory denotes the percentage of green pixels to the total pixels within a given street-view image of a certain location

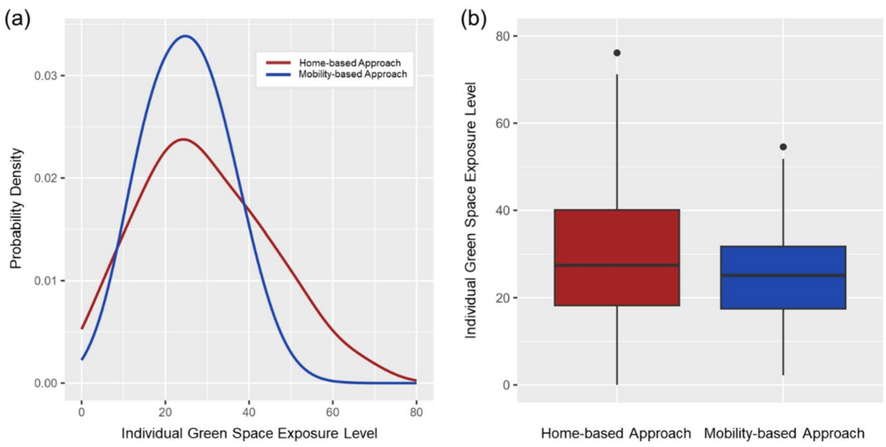

Fig. 3 **a** Probability density functions and **b** box plots of individual home- and mobility-based levels of green exposure of the entire sample (n = 31,862)

(Table 2), with a significantly lower average green exposure level for the mobility-based approach than for the home-based approach. Additionally, the standard deviation for the mobility-based approach is also smaller than that of the home-based approach regardless of neighborhood types and sizes, implying that NEAP is observed in all neighborhood types and sizes.

However, the magnitude of the difference between mobility and home-based exposure levels depended on the neighborhood. For instance, in rural areas, the difference between the mobility- and home-based exposure levels was 6.660; in suburban areas, was 2.996. Similarly, large urban areas showed a difference of 5.463 in contrast to small urban areas, where the observed difference was 2.771. These variations underscore the nuances in the relationship between green exposure levels and neighborhoods regarding types and sizes (i.e., spatial non-stationarity), which we will investigate in the next section, with special attention to inequality in green exposure. Figure 4 illustrates the box plots of individual green exposure levels in terms of neighborhood types and sizes.

3.2 Inequality analysis

We computed Gini indices for both home- and mobility-based green space exposure levels and compared them in terms of neighborhood types and sizes (Table 3). In our analysis of the sample (n = 31,862), we observed that the Gini index for home-based green space exposure was 0.301, while for mobility-based exposure, it was 0.212. This disparity indicates that inequality is more pronounced when assessed through the home-based approach for the entire sample. This suggests that when accounting for the mobility-based approach, the disparities decrease. This aligns with the NEAP's "averaging" effect, which indicates individual exposure levels tend to converge toward the average level of the population (Kwan 2018a). Furthermore,

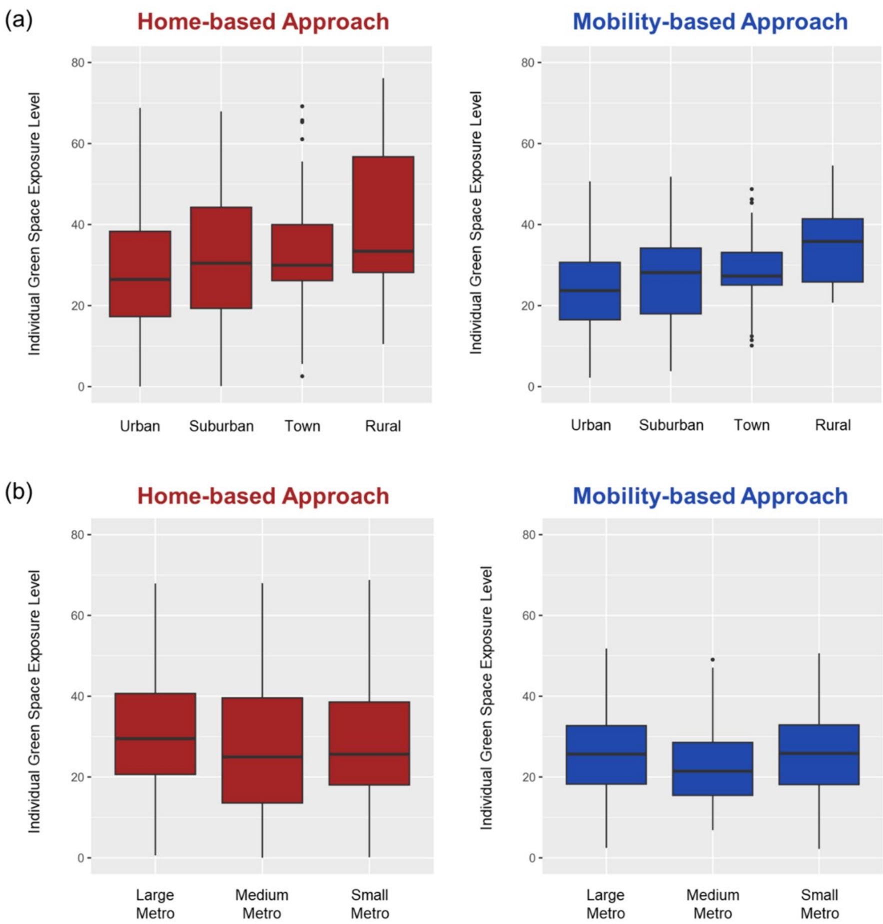

Fig. 4 Boxplots of individual home- and mobility-based green exposure levels in terms of neighborhood **a** types and **b** sizes

it implies that assessing inequality using the home-based approach tends to overestimate inequality.

We observed a consistent trend when examining Gini indices for specific subsamples categorized by neighborhood type and size (Table 3). The Gini indices calculated from individual mobility-based green exposure levels for all neighborhood types and sizes were smaller than those derived from home-based exposure. The differences in Gini indices between home- and mobility-based approaches, however, differed slightly among the subsamples. For example, in suburban areas, the Gini index decreased by 0.060 when using the mobility-based approach, but in urban, town, and rural areas, the decrease was more substantial at approximately 0.100. Similarly, in large urban areas, the decrease was 0.060; on the contrary, in medium-sized areas, it was 0.127. Thus, using only a home-based approach tends to overestimate the inequality in green space exposure, with more significant implications for

Table 3 Gini indices of home- and mobility-based individual green exposure levels in terms of neighborhood type and size

	Gini index of individual home-based green exposure levels	Gini index of individual mobility-based green exposure levels	Difference
Entire sample ($n=31{,}862$)	0.301	0.212	0.089
Neighborhood type			
Urban ($n=22{,}108$)	0.315	0.214	0.101
Suburban ($n=7120$)	0.270	0.210	0.060
Town ($n=2225$)	0.230	0.133	0.097
Rural ($n=409$)	0.254	0.146	0.108
Neighborhood size			
Large ($n=10{,}497$)	0.270	0.210	0.060
Medium ($n=8954$)	0.343	0.216	0.127
Small ($n=9777$)	0.304	0.211	0.093

urban, town, and rural neighborhoods than for suburban neighborhoods as depicted in our results. Moreover, the inaccuracy caused by overlooking mobility is more significant for medium-sized urban neighborhoods than for small and large ones. These findings suggest spatial non-stationarity, emphasizing the importance of considering different study areas pertaining to neighborhood sizes and types for accurately characterizing inequalities in green space exposure.

Next, we report the correlation coefficients of the relationship between levels of individual green exposure and the social vulnerability index (SVI). Table 4 reports the correlation coefficients, and Figs. 5, 6 and 7 illustrate the scatter plots with a trend line (i.e., linear regression model). For the entire sample ($n=31{,}862$), the correlation coefficient between home-based individual exposure levels and the SVIs is -0.122 ($p<0.001$), indicating that people with higher social vulnerability have lower exposure to green spaces in their home neighborhoods. When mobility is considered, the magnitude of the correlation coefficient slightly decreased to -0.109 ($p<0.001$), which may be attributed to the averaging of the green space exposure that consequently reduces the overall disparity in green exposure levels (Fig. 5).

In urban and suburban neighborhoods (Fig. 6), the results did not show substantial deviations from the correlation analysis of the entire sample, suggesting similar relationships among the variables. However, for the subsample living in town neighborhoods, the size of the correlation coefficient substantially increased in mobility-based exposure levels (-0.188) compared to home-based exposure levels (-0.047). This suggests that environmental inequality could be underestimated in towns when only home-based exposure is used to evaluate the inequality, which reports the contrast pattern to the global model result. Moreover, for residents of rural areas, the relationship between SVI and green space exposure presented contrasting patterns. Findings based on the home-based approach revealed that neighborhoods with higher SVI scores were associated with higher levels of green space exposure. This suggests that, within the rural context, the issue of environmental inequality might

Table 4 Correlation coefficients of home- and mobility-based individual green exposure levels and SVI regarding the neighborhood types and sizes

	Home-based exposure	Mobility-based exposure	Coefficients comparison between home- and mobility-based approaches	
			Direction	Intensity
Entire sample ($n=31,862$)	−0.122***	−0.109***	Same	Reduced
Neighborhood type				
Urban ($n=22,108$)	−0.130***	−0.117***	Same	Reduced
Suburban ($n=7120$)	−0.181***	−0.147***	Same	Reduced
Town ($n=2225$)	−0.047***	−0.188**	Same	Increased
Rural ($n=409$)	0.209***	−0.041	Different	Reduced
Neighborhood size				
Large ($n=10,497$)	−0.346***	−0.372***	Same	Increased
Medium ($n=8954$)	−0.042***	0.068***	Different	Increased
Small ($n=9777$)	−0.075***	−0.142***	Same	Increased

*** denotes $p<0.001$. ** denotes $p<0.01$

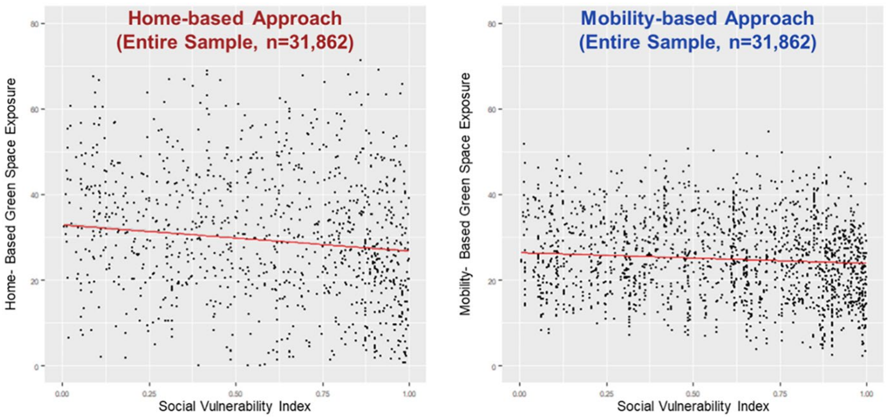

Fig. 5 Scatter plots with x-axis values (Social Vulnerability Index scores) and y-axis values (home- and mobility-based individual levels of green exposure) of the entire sample. (Note: Lines in the scatter plots indicate the linear regression line.)

not be as pronounced as in urban and town neighborhoods. Similarly, in terms of the mobility-based exposure assessment, the results indicated an insignificant association between SVI and exposure levels.

In terms of neighborhood size, for walk commuters living in small and large neighborhoods, the size of the correlation coefficients is bigger in mobility-based than for home-based exposure levels (Fig. 7). This suggests that people living in more vulnerable neighborhoods are less exposed to green spaces on

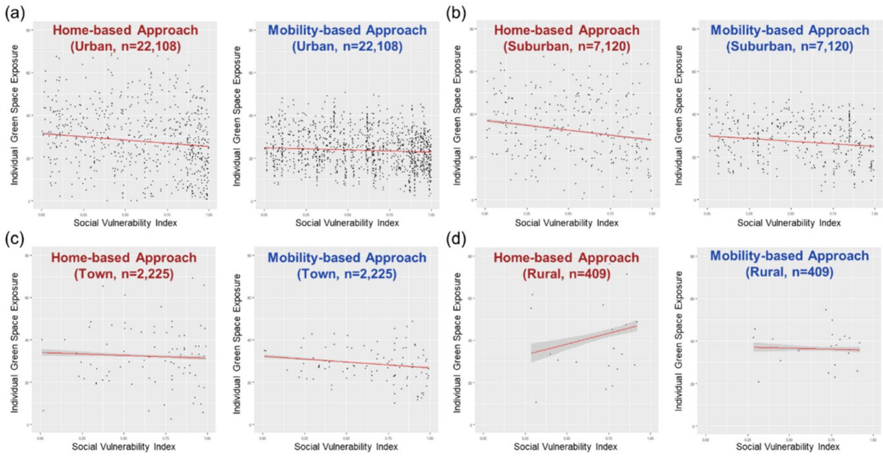

Fig. 6 Scatter plots with x-axis values (Social Vulnerability Index scores) and y-axis values (home- and mobility-based individual green exposure levels) of individuals living in **a** urban, **b** suburban, **c** town, and **d** rural neighborhoods. (Note: Lines in the scatter plots indicate the linear regression line.)

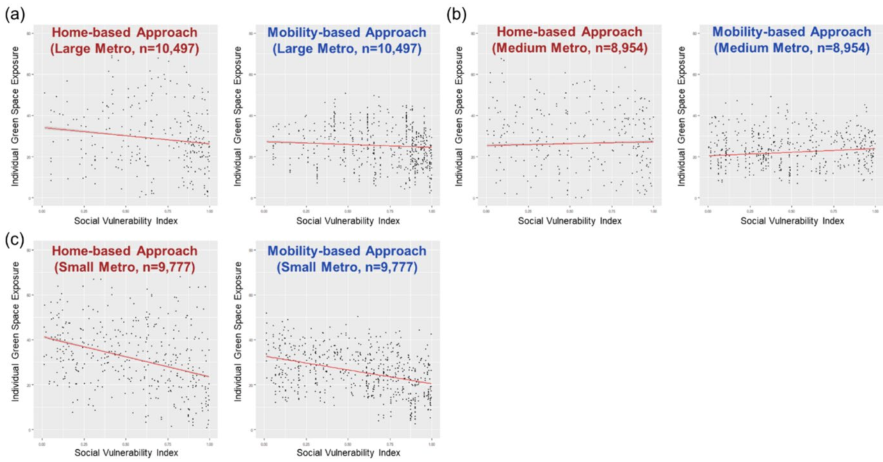

Fig. 7 Scatter plots with x-axis values (Social Vulnerability Index scores) and y-axis values (home- and mobility-based individual green exposure levels) of individuals living in **a** large-sized, **b** medium-sized, and **c** small-sized urban and suburban neighborhoods. (Note: Lines in the scatter plots indicate the linear regression line.)

their walk-based commutes. Moreover, exposure inequality assessed based on the home-based exposure assessment tends to underestimate inequality in terms of the SVI. However, the subsample residing in medium-sized neighborhoods reported a different pattern. When the mobility-based exposure level was considered, higher social vulnerability was associated with greater exposure to green space. Overall, these findings highlight the complex relationship between individual exposure to green space and neighborhood type and size; they also underscore the necessity for a local-specific approach when estimating inequality in people's exposure to green spaces.

4 Discussion

Our study lends substantial empirical support to the neighborhood effect averaging problem (NEAP), an important methodological challenge in exposure assessment studies (Huang and Kwan 2022; Kim and Kwan 2019, 2021a; Kwan 2018a; Ma et al. 2020; Tan et al. 2020; Wang et al. 2024). Our findings correspond with previous studies, which suggest that an individual's broader mobility patterns beyond their residential areas can significantly affect their overall environmental exposure (Kim and Kwan 2021a, b; Lu 2021, 2023; Lu and Habre 2023; Wang et al. 2021). The results also demonstrate that inequality in green space exposure can be reduced when we consider mobility-based exposure for our entire sample ($n = 31{,}862$).

Green spaces tend to be unevenly distributed, with economically disadvantaged communities and racial minorities having less exposure to green exposure in their residential neighborhood (Bruton and Floyd 2014; Nesbitt et al. 2019; Sharifi et al. 2021). These socially vulnerable populations might want to compensate for their limited access to green space by traveling more frequently and further distances to a better environment (Muñiz et al. 2013). This compensatory consumption of green spaces implies that people dissatisfied with their residential surroundings tend to allocate a significant proportion of their time for leisure travel to greener surroundings (Naess 2006). Therefore, an exposure assessment approach that is limited to people's residential neighborhoods may fail to paint a complete picture of people's interaction with green spaces. These findings illuminate the importance of incorporating a mobility-based approach into studies and policy implications pertaining to green space exposure. By doing so, we can achieve a more comprehensive and accurate assessment of green space exposure, aiding in the development of effective strategies for urban planning and public health (Sharifi et al. 2021; Wang et al. 2021).

Our findings also contribute critical insights into spatial non-stationarity, revealing differential relationships between social vulnerability and green space exposure based on neighborhood type and size. This may be attributed to variations in the spatial distribution of green spaces and commute travel patterns across neighborhoods (Kim and Kwan 2019, 2021a; Lee et al. 2023; Li and Liu 2016). For instance, rural areas inherently have more abundant green space because of lower population density and development, which could increase their residents' green exposure levels, irrespective of vulnerability. Dennis and James (2016) showed that rural neighborhoods have a notably higher green space cover per person, significantly overshadowing their urban and suburban counterparts. Similarly, green space exposure and its associated health benefits may also vary across urbanization levels based on the built environment. A study conducted by Huang and colleagues on green space and COVID-19 transmission in Hong Kong found that in highly populated urban regions, the presence of green spaces had a negative correlation with the risk of COVID-19 because green areas helped to decrease the density of high-risk venues and limit potentially risky human interactions (Huang et al. 2020). In contrast, in less densely populated suburban areas, a positive association was observed because suburban green spaces often included country parks that attracted many people interested in outdoor activities like hiking and picnicking during lockdowns (Huang et al. 2020).

Therefore, our results imply that a global model might not sufficiently capture the local intricacies of green space exposure. As Kwan (2021) argued, the interactions of factors in the local context emphasize the potential for misinterpretation when generalizing findings in health-environment relationships. Therefore, acknowledging the importance of non-stationarity can help avoid erroneous findings and uncover valuable local insights that are often overlooked in global-level studies (Kwan 2021). From a policy perspective, our findings highlight the necessity to acknowledge and incorporate unique local contexts and data on mobility patterns and green spaces when designing interventions to address green space inequality.

Furthermore, given that studies on green space exposure and inequality were conducted mainly in large cities (Bertram and Rehdanz 2015; Duan et al. 2018; Jennings et al. 2017; Sánchez et al. 2021; Wu and Kim 2021), policy recommendations derived from such studies are potentially ill-suited for smaller neighborhoods (e.g., rural and town communities) given the spatial non-stationarity of green space exposure and its inequality. This methodological challenge may be additionally complicated by the limited resources available for policy implementation in smaller areas (Astell-Burt et al. 2014; Barnidge et al. 2013; Zhang et al. 2022). The failure to address these challenges consequently exacerbates the existing inequality in green space exposure and associated health benefits between large cities and under-examined areas, such as small- and medium-sized cities and rural areas (McConnachie and Shackleton 2010; Wolff et al. 2020). The identified research and policy gaps for these underrepresented regions present an important issue that needs to be addressed urgently. It is crucial to extend the scope of green space inequality research beyond large cities and formulate contextual policy recommendations for under-examined study areas, such as small- and medium-sized cities and rural communities (Abner et al. 2016; Kim and Jang 2023). This will lead to a more accurate assessment of green exposure inequality and identify the local neighborhoods to be prioritized, eventually leading to a more equitable distribution of the benefits derived from green space exposure (Peng et al. 2022; Xu et al. 2018).

Our study has several limitations that future studies can address. The first is that our mobility-based exposure assessment is based on the shortest travel time paths. However, in reality, people might deviate from the shortest travel time routes (Guo and Loo 2013; Miranda et al. 2021). Similarly, the unavailability of data precluded us from incorporating the amount of time individuals spent at home and in the workplace. Failure to account for the temporal dimension of individuals' exposure to green spaces might compromise the reliability of our research outcomes and increase contextual uncertainties, as the amount of time individuals spent in residential neighborhoods significantly influences their exposure to environmental factors (Kwan 2012, 2018b). This limitation can be addressed by leveraging location-aware smart devices, such as GPS, mobile phones, environmental sensors, and accelerometers (Bireboim et al. 2021; Liu et al. 2023; Marquet et al. 2022; Mears et al. 2021; Sagl et al. 2015; Wang et al. 2018), which enable precise identification of individuals' space–time trajectories, exposure frequency, and length of time spent in green spaces (Kwan 2012, 2018b).

Additionally, because of geoprivacy issues, we could not obtain precise geographic coordinates of daily activity-travel patterns of the sample but utilized home-to-work data that were aggregated to a TAZ level. Additionally, although homes and workplaces are major anchor points of individuals' daily activity-travel patterns (Sprumont and Viti 2018; Wang and Ozbilen 2020), this approach might not produce a detailed picture of people's daily activity-travel patterns related to green space exposure (Kim and Kwan 2019). Future studies may consider employing daily GPS trajectory data or surveys (Haybatollahi et al. 2015; Kabisch and Haase 2014) that provide more precise information on individuals' daily trajectories. However, it should be noted that it is practically challenging to obtain detailed daily activity-travel data for multiple cities because of limited data availability. Therefore, we argue that, even if this study focused on home-work trips and overlooked non-work trips, the fact that this study investigated multiple regions—urban, suburban, town, and rural areas—in three states could overcome the limitations.

Another limitation is the seasonal variation and time inconsistency in the GSV images might affect the GVI values obtained (Li et al. 2015). For instance, the GSV images taken in winter (or other seasons) may not provide a correct representation of the availability of green space. This can be problematic for small- and medium-sized cities where GSV images have limited spatial coverage and high temporal variability (Curtis et al. 2013; Fry et al. 2020; Kim and Jang 2023). Infrequent updates and temporal inconsistencies in when street-view images are captured might result in inaccurate representation of true green spaces. Future studies can utilize alternative sources, such as crowdsourced images (Giuliani et al. 2021; Zheng and Amemiya 2023), to mitigate the temporal inconsistency of Google images.

Moreover, our exposure assessment approach might not fully reflect individuals' true exposure to green space and their experience. On the one hand, some studies have argued that even though disadvantaged populations can access green spaces, the quality of those green spaces might be inferior (Boone et al. 2009; Rigolon et al. 2021). Future studies can overcome this limitation by considering a variety of elements of the quality of green spaces, such as the color of vegetation (Xu et al. 2023). Furthermore, our study has focused on the spatial non-stationarity across varying neighborhood types and sizes. However, using geographically weighted regression (GWR) can help us identify the spatial non-stationarity within an urban or rural area (Mao et al. 2018; Li et al. 2019), which has not been implemented in our study. For the correlation analysis between an individual's green space exposure and social vulnerability, we used SVI as a proxy to measure the sampled individual's socioeconomic characteristics. Although it would have been ideal to utilize individual-level socioeconomic data for analysis, such data are not available, so SVI value at each individual's home location was assumed to be ab indicator of sociodemographic status. Future studies can use individual-level sociodemographic data by undertaking surveys and conducting multivariate regression analysis to control covariates and provide more robust findings on socioeconomic disparities in green space exposure.

Despite these limitations, our study makes a significant contribution to the literature on exposure to green space. Specifically, our findings significantly contribute to recently growing literature on the neighborhood effect averaging problem (NEAP), a crucial methodological problem (Kwan 2018a) in exposure assessment studies (Huang and Kwan 2022; Kim and Kwan 2019, 2021a, 2021b; Kwan 2018a, b; Ma et al. 2020; Tan et al. 2020; Wang et al. 2024). We highlighted the difference between the home- and mobility-based exposure levels, offering crucial empirical evidence for the NEAP. More importantly, our research sheds light on the patterns of inequality in exposure that vary for different neighborhood types and sizes, suggesting the spatial non-stationarity issue. In other words, this comparative study of multiple towns and cities that are diverse in geographic and socioeconomic contexts expands our fundamental understanding of the NEAP by addressing the issue of spatial non-stationarity. This is a unique contribution of our study to a growing body of geographic studies on the assessment of green space exposure.

Overall, our results emphasized the importance of considering mobility in exposure assessments and the spatial non-stationarity issue in such studies, which calls for attention to conducting local-specific studies. This study has important policy implications because it contributes to the formulation of local environmental policies that mitigate inequality in green space exposure. Our results illustrate that global-level results (e.g., inequality assessments) might not be accurately translated into each locality because of spatial non-stationarity. Thus, to formulate effective local-level environmental and urban planning policies, our results call for the collection of local-level data and conducting of local-level analyses. The nuanced understanding would contribute to more effective strategies to address inequality in green space exposure, thus fostering a healthier and more equitable environment for all.

5 Conclusion

Our study estimated the levels of home- and mobility-based green space exposure of 31,862 walk commuters in the states of Virginia, Kentucky, and West Virginia in the USA. The deep learning-based semantic segmentation technique was used to extract green spaces from commercial street-view images, which were then utilized to estimate individuals' levels of green exposure. Gini indices and correlation coefficients were obtained to examine the inequality in green space exposures in terms of neighborhood type and size. The results showed that people's mobility-based exposure levels are significantly lower than their home-based exposure levels. The overall inequality in exposure levels—as measured by Gini indices—reduced when people's mobility was considered compared to the inequality based on home-based exposure levels. Correlation coefficients between individual exposure levels and their social vulnerability indices demonstrated mixed and complex patterns regarding neighborhood type and size, demonstrating the presence of spatial non-stationarity. Taken together, our results emphasized the importance of considering mobility in exposure assessments and the spatial non-stationarity issue in such studies. This calls for conducting local-specific studies, which can contribute to developing local planning and public health policies that intend to alleviate inequality in green space exposure.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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